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Mapping of climate vulnerability of the coastal region of Bangladesh using principal component analysis

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ABSTRACT

The coastal region of Bangladesh is highly vulnerable due to its low adaptive capacity, dense population, flat topography and exposure to various natural disasters such as cyclone, storm surges, sea level rise, tidal floods, bank erosion etc. In addition to present vulnerability, climate change will bring detrimental impact on socio-economic performance, health, and livelihood of the coastal population. This study has been conducted to assess the vulnerabilities of the coastal region of Bangladesh by considering the IPCC framework of vulnerability studies and using multivariate statistical techniques. A total of 31 indicators have been used of which 24 are socio-economic and 7 are natural (exposure) indicators and these indicators have been retrieved from the secondary source. Principal Component Analysis (PCA) has been applied to find unequal weights of all indicators. Afterward, 7 vulnerability groups (Principal Components - PCs) have been retained which eigenvalue greater than one in accordance with Kaiser Criterion. Demographic Vulnerability (PC1), Economic Vulnerability (PC2), Agricultural Vulnerability (PC3), Water Vulnerability (PC4), Health Vulnerability (PC5), Climate Vulnerability (PC6) and Infrastructural Vulnerability (PC7) are the principle vulnerable groups considering both present (2013) and the future (2050) climate change scenarios. Spatial maps of each group have been generated to assess the regional variation of above mentioned multispectral vulnerability profile across the coastal region of Bangladesh. Climate change will change dramatically the future vulnerability profile which will be alarming for agro-ecological systems of that region. The findings of this study might be useful for policy makers as well as planners.

1. Introduction

Bangladesh has marked as one of the most vulnerable countries in the world considering climate change issues. Bangladesh has been characterized by extreme climatic events (Ahmed, Occhipinti-Ambrogi, & Muir, 2013; DoE, 2012) with an area of 147,570 km^2 (BBS, 2013) and a rapidly growing population currently stands at over 160 million (Dewan, Yamaguchi, & Rahman, 2012; DoE, 2012) as well as expected to be near 180 million by 2025 (Shaw, 2015). The population density of the country is very high which is currently stands as 1015 per sq. km. with an annual growth rate of 1.37 percent (Shaw, 2015). By 2025, population density could be over 1200 per km^2 (Shaw, 2015). The lower-lying coastal districts of the Bay of Bengal are highly vulnerable to extreme climate condition, including changes of episodic disasters such as cyclone-induced storm surge, coastal floods, river bank erosion, and increasing trend of sea level rise, saline water intrusion and many more natural calamities (Dasgupta et al., 2014).

Though vulnerability assessment is not a new concept, recently it emerges in the climate science and climate policy application (Füssel & Klein, 2006) which is the first step in minimizing the impact of the future extreme climate based on socio-ecological system (Adger, 2006; Howden et al., 2007). Vulnerability provides the foundation for risk level assessment as well as building resilience (Salinger, Sivakumar, & Motha, 2005). Assessing vulnerability to climate change is important for characterized the risks posed by climate change and delivers information for recognizing measures in order to adapt to the adverse impacts of climate change. It is also the degree to which a system either susceptible or incapable to cope with the adverse effects of climate change, including climate variability and extremes (Field et al., 2014; IPCC, 2001). This assessment of vulnerability will facilitate

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stakeholders and decision-makers to mark the most vulnerable areas, the most vulnerable social groups and the most vulnerable sectors. On the other hand, sensitivity is the degree to which a system is experienced with positive and negative by directly or indirectly of all elements of climate changes (McCarthy, 2001). Adaptive capacity is the ability of a system to cope with extreme climate variability and to moderate the potential damages (McCarthy, 2001; IPCC, 2001; Burton, Huq, Lim, Pilifosova, & Schipper, 2002; Adger, 2006; Brooks, 2003; Gallopín, 2006; Yohe & Tol, 2002; Gerlitz, Banerjee, Brooks, Hunzai, & Macchi, 2015). The vulnerability of a system is determined by these three components: i) the presence of people, livelihoods, species or ecosystems, environmental functions, services, resources, infrastructure, or economic, social or cultural assets in places and settings that could be adversely affected (exposure), ii) the degree to which the system is affected (sensitivity) and iii) the ability of the system to adjust to potential damage (adaptive capacity) (IPCC, 2014).

Coastal region has been marked as vulnerable due to the impacts on water quantity and quality from various activities such as continuing high density of socio economic activities, rising of sea level, enhancing saltwater intrusion (Iyalomhe et al., 2015) as well as rising of temperature and changing of both cyclone and precipitation patterns (Moser & Davidson, 2015). Global Climate Model results have been used for assessing the agricultural impact of climate extreme events (Glibert et al., 2014; Iyalomhe et al., 2015) and sea level rise and storm surge (Neumann, Emanuel, Ravela, Ludwig, & Verly, 2015), coastal erosion (Barbier, 2015). It has found that the agricultural sector of the southern part in Bangladesh is severely affected by extreme climate under the higher emission scenarios (Ruane et al., 2013). The assessment of vulnerability due to coastal inundation in present and the future scenarios from sea level rise would be useful for assessing options of climate change adaptation (McInnes, Macadam, Hubbert, & O'Grady, 2013). In the context of climate change, assessment of current and future vulnerability due to coastal inundation is found essential (McInnes et al., 2013). Vulnerability assessment should consider the interaction among natural processes, socio-economic conditions, and the mechanisms of responses of the integrated ecological and economic system (Chang & Huang, 2015).

Several studies put a separate emphasis by constructing coastal community using vulnerability indexes (Cinner et al., 2013; Bjarnadottir, Li & Stewart, 2011) to assess the vulnerability. In Bangladesh, the socioeconomic vulnerability index (Ahsan & Warner, 2014; Hagenlocher, Delmelle, Casas, & Kienberger, 2013; Chen, Cutter, Emrich, & Shi, 2013; Ge et al., 2013; Eakin & Luers, 2006; Yoon, 2012) has been prepared for the 7 unions[1] of *Koyra* Upazila (sub-district) in the southwestern coastal region through household survey. It has been found that the southern and south eastern unions are relatively more vulnerable (Ahsan & Warner, 2014). The drinking water quality and management vulnerability during extreme climate events have been assessed in rural areas of the coastal region of Bangladesh (Delpla et al., 2014; Sarkar & Vogt, 2015). The water vulnerability in relation to global climate change provides the community a comprehensive overview of the lack of water availability to identify the specific areas where attention is needed (Plummer, de Grosbois, Armitage, & de Loë, 2013) because adequate safe drinking water supply is essential for economic, social and sanitary reasons (Pagano, Giordano, Portoghese, Fratino, & Vurro, 2014). On the other hand, infrastructure vulnerability involves the consideration of a range of physical, operational, geographical and socio-economic characteristics (Grubesic and Matisziw, 2013) and extreme climatic events which resulted impact on residents and transportation infrastructure in the northeastern coastal region (Tang et al., 2013) and incorporate economic value of infrastructure, and residential and commercial building values (Thatcher, Brock, & Pendleton, 2013).

Several tools and techniques are available for assessing vulnerability in a particular region. One such tool is the vulnerability assessment through mapping as it is a powerful visualization tool to identify the most susceptible from present to future changes in the environment (Abson, Dougill, & Stringer, 2012). The vulnerability mapping by hotspot identification (Davies & Midgeley, 2010; Ericksen et al., 2011) makes easy for decision making of government, donor agencies of Southeast Asian countries which are the most vulnerable to climate change (Yusuf & Francisco, 2009). In multivariate statistics, Principal Components Analysis (PCA) is a mainstay of modern data analysis tool that is widely used (Blasius and Greenacre, 2014; Bro & Smilde, 2014; Hair, Black, Babin, Anderson, & Tatham, 2006; Hou, Li, & Zhang, 2015; Kline, 2014; Shlens, 2014; Yeater, Duke, & Riedell, 2015) to depict the profile of vulnerability (Kang, Xuxiang, & Jing, 2015; Guillard-Gonçalves, Cutter, Emrich, & Zêzere, 2015; Singh & Vedwan, 2015) in making decisions based on spatial maps (Okey, Alidina, & Agbayani, 2015; Schiavinato & Payne, 2015). PCA approach provides several potential advantages. When the original variables are correlated, the higher orders Principal Components (PCs) is able to capture more of the total variability in the original data than any individual original variable. PCA technique is applied for spatially explicit aggregation of socioeconomic vulnerability (Miller, 2014), poverty (Howe, Suich, van Gardingen, Rahman, & Mace, 2013) and health vulnerability (Fisher, Ellis, Adams, Fox, & Selig, 2015; Zhu et al., 2014).

In this study, principal components (PCs) has been used to identify the socio, economic and environmental based vulnerabilities through mapping in the coastal region of Bangladesh. PCA approaches to vulnerability mapping have been applied to identify the hotspot of high vulnerability within the study area. The spatial mapping for addressing the vulnerability of population dynamics in the coastal region of Bangladesh with the complex agro-ecological system has been investigated. For examining the spatial variation of vulnerability, indicators related to socio-economic, agricultural, water, health, climate, and environment have been considered. Taking national policy implication, it is essential to know the spatial and regional explicit variation of the vulnerable profile which is more vulnerable region under extreme climate conditions. Hence, to guide the development initiatives of the country, spatial vulnerability mapping in the coastal region of Bangladesh has been developed.

2. Study area

The coast of Bangladesh is about 710 km long and consists of 20 districts having 140 Upazilas. Most of the coastal Upazilas in the 20 districts have elevations about 1.2–4.5 m above mean sea level. These districts are directly or indirectly affected by various natural or man-made events. The total coastal area is about 47,201 km^2 (WARPO, 2006) which lies within the tropical zone between 21 23″ N and 89 93″ E.

In subtropical climate, summer extends from March to May followed by monsoon from June to September and winter months from November to February. Agriculture is the primary source of economy and major land is used in the agricultural sector. Most of the coastal region is covered with high population density, notably Chittagong and Khulna city occupied with more than 20,000 populations per sq. km (Fig. 1).

3. Materials and methods

3.1. Indicator based vulnerabilities assessment

The coastal belt of Bangladesh has been selected as the study area. The vulnerability profile has been developed for baseline scenarios and for the future scenarios considering climate change. Year 2013 has been

[1] Union is the smallest administrative and local government unit in Bangladesh. There are 4553 Unions in Bangladesh in 492 Upazilas (sub-district, formerly called Thana, is an administrative region in Bangladesh). There are 492 Upazilas in 64 Districts in Bangladesh.

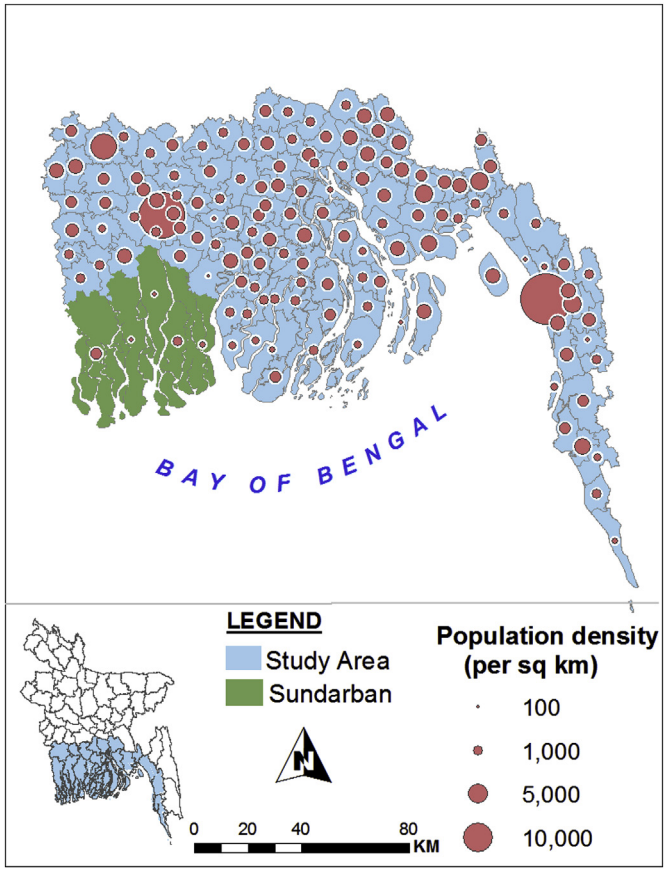

Fig. 1. Study area map of the coastal region of Bangladesh with population density.

considered as baseline due to the availability of various social and economic data of the study area. Year 2050 has been considered as the future scenarios as short to the medium time frame is preferred by the policy makers for this region. Many studies have been conducted using social, economic or biophysical indicators to assess vulnerability (Liu et al., 2008; Metzger & Schröter, 2006; Stelzenmüller, Ellis, & Rogers, 2010). This study considers only population projection as a basis for the change of the socio-economic indicators in the future. Except for the population projection, there have been no adequate data available which can provide the possible changes of the socio-economic indicators. Also, all the socio-economic indicators are normalized based on the population of the Upazila. Therefore, projected changes of the population may provide a basis for the change of the socio-economic indicators. For the assessment of coastal vulnerability, the socio-economic and biophysical indicators has been retrieved from the secondary sources including published reports and journals. Next two sub-sections provide the detail description of these indicators, along with their sources.

3.2. Socio-economic indicators

A total of 24 socio-economic and 7 biophysical indicators has been considered for this study. Data for socio-economic indicators have been obtained from the Bangladesh Bureau of Statistical Yearbook (BBS, 2013), while biophysical indicators are collected from various reports, journals, articles, and maps. These collected data have been checked and normalized before conducting a multivariate statistical analysis. A brief description of the selected indicators is given in Table 1. The rationale of selecting all these socio-economic indicators is presented in Table 2. The population density driver is considered for the future projection of socio economic indicators and this study adopts the cohort-component method of population projection (Hollmann, Mulder, & Kallan, 1999; Raftery, Li, Ševčíková, Gerland, & Heilig, 2012; Spencer, 1984). Commonly the subjective, objective and structural model are used for population projection (Smith, Tayman, & Swanson, 2006; Preston, Heuveline, & Guillot, 2000). However, the present study adopts cohort component method with an alternative assumption for future fertility and mortality. The country's populations are grouped into cohort statistical table for the future population of the study area by individual age and sex (Booth, 2006; Spencer, 1984). Population in Bangladesh in the year 2050 is assumed nearly 222 million (World Population Data Sheet, 2012).

3.3. Biophysical indicators

The 7 biophysical system indicators for the present base scenario have also been classified based on the collected information from different sources and literature. A brief description of the biophysical indicators is provided in Table 1. The rationale of selecting these biophysical indicators is provided in Table 2. For most of the cases, the data were collected from maps of different study reports and research articles. The maps were digitized and overlaid with the coastal Upazila map using a GIS tool to determine the values of the respective indicator. Then the data were classified according to vulnerability range from 1 to 5. Inundation due to storm surge in the coastal Upazilas has been derived from an inundation risk map developed by IWM (2009) (Supp. Fig. 1). The flood risk exposure map for the 24-h inundation of Bangladesh was obtained by a study of World Bank (2010) (Supp. Fig. 2). Shoreline erosion and accretion have been obtained from the study conducted by Sarwar and Woodroffe (2013) (Supp. Fig. 3). Salinity intrusion due to sea level rise for the present scenario has been obtained from a study conducted by Centre for Environmental Geographic Information Service (MOEF, 2009) (Supp. Fig. 4). The 1- day maximum rainfall data collected from Bangladesh Meteorological Department (BMD) for 23 stations of the duration 1981–2010 to generated interpolated risk map. The map of the digital elevation model (DEM) of the coastal region at a 50 m resolution has been collected from IWM (2014).

Future changes in salinity intrusion, maximum 1-day precipitation, flood inundation considering climate change have been developed based on the climate projections in 2050 and secondary information. Inundation map due to storm surges considering climate change projections in 2050 was generated from World Bank (Dasgupta et al., 2010) (Supp. Fig. 5). Flood risk exposure map for climate change scenario in 2050 was developed considering changes in temperature and precipitation levels and increases in the sea level (World Bank, 2010) (please see Supp. Fig. 6). Salinity intrusion for different sea level rise projection map was used for possible future changes of salinity (MOEF, 2009) (please see Supp. Fig. 4). Future 1-day maximum rainfall data has been collected from the regional climate model predictions for the RCP 8.5 scenarios in 2050 over the CORDEX-SA domain. Finally, the risks maps of biophysical indicators are digitized and overlaid with the coastal Upazila maps using the GIS tool to determine the values of the respective indicator for each Upazila.

3.4. Normalization of the indicators

Normalization is important for multivariate statistical analysis as some variables have large range of variance and some of them have a small range of variance. Normalization technique that implies the transforming dataset to a specific range (0–1) is thus essential. Normalization technique has been applied to create a more robust relationship amongst the dataset and imply to normalize residuals using the methods of transformation (Quackenbush, 2002). To avoid the influence of one variable to other variables, the dataset has been normalized. A similar approach has been followed in developing human development index and life expectancy index (Coulibaly et al., 2015; Piya, Maharjan, & Joshi, 2012; UNDP, 2007). Data normalization has

Table 1
Description of socio economic and biophysical drivers for vulnerability assessment.

Dimension	Sl.	Indicators	Description	Unit	Data source
Socio-economic driver	1	Density of population	Sensitive	people/sq.km	Bangladesh Bureau of Statistics (BBS, 2011)
	2	Male-female ratio	Sensitive	male/100 female	
	3	Literacy Rate	Adaptive Capacity	percentage	
	4	Gender gap in literacy rate	Sensitive	percentage	
	5	Percentage of disable	Sensitive	percentage	
	6	Source of drinking water	Adaptive Capacity	number/1000 of population	
	7	Electricity connections	Adaptive Capacity	number/1000 of population	
	8	Poverty	Sensitive	percentage	
	9	Access to transport facilities	Adaptive Capacity	number/1000 of population	
	10	Medical institutions	Adaptive Capacity	number/1000 of population	
	11	Govt. primary schools	Adaptive Capacity	number 1000 of population	
	12	Motor vehicles	Adaptive Capacity	number/1000 of population	
	13	Railway and water way	Adaptive Capacity	km/1000 of population	
	14	Embankment roads	Adaptive Capacity	km/1000 of population	
	15	Cyclone shelters	Adaptive Capacity	number/1000 of population	
	16	Flood shelters	Adaptive Capacity	number/1000 of population	
	17	Un- metalled roads	Adaptive Capacity	km/1000 of population	
	18	Co-operative societies	Adaptive Capacity	number/1000 of population	
	19	Growth centers	Adaptive Capacity	number/1000 of population	
	20	Irrigation by power pumps	Adaptive Capacity	number/1000 of population	
	21	Production of rice	Adaptive Capacity	metric ton	
	22	Nationalized and private banks	Adaptive Capacity	number/1000 of population	
	23	Insurance companies	Adaptive Capacity	number/1000 of population	
	24	Bank loan	Adaptive Capacity	number/1000 of population	
Biophysical driver	25	Storm sure inundation	Exposure	m	Published Reports, Journal articles and maps
	26	Inundation due to floods	Exposure	m	
	27	Shoreline erosion	Exposure	m/year	
	28	Shoreline accretion	Exposure	m/year	
	29	Coastal elevation	Exposure	cm	
	30	1-day maximum rainfall	Exposure	mm	
	31	Salinity intrusion due to SLR	Exposure	Percentage (%)	

been done using the following equation (Eq. (1)).

$$\text{Index, } X_d = \frac{X_d - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where, x_d is an observed value in an array of observed values for a given variable; x_{max} is the highest value in the same array; x_{min} is the lowest value in the same array.

3.5. Principal component analysis (PCA)

The principal component analysis is used by many scientific disciplines. PCA is a statistical procedure that applies an orthogonal transformation in order to convert a set of observations which might be possibly correlated variables into linearly uncorrelated variables called principal components. This transformation is conducted in such a way that the first principal component has the largest possible variance, and each of the next principal components has the highest variance possible following the constraint that it is orthogonal to the preceding components. Finally, the resulting vectors produced by PCA are an uncorrelated orthogonal basis set.

In mathematically the PCA depends on the Eigenvector based multivariate analysis (Abdi & Williams, 2010). The principal component analysis can be done by eigenvalue decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix. The results of a PCA are usually presented in terms of component scores, which is often known as factor scores (the transformed values of variable related to a particular data point), and loadings (the weight used to multiply each standardized original variable in order to get the component score) (Wold, Esbensen, & Geladi, 1987).

The quality of PCA can be evaluated by cross-validation using either bootstrapping or jackknife method (Abdi & Williams, 2010). However, the application of PCA implies to maximize the variance of a simple linear combination in a direction orthogonal to the first principal component (PC) and so on. For example, the first principal component analysis could be used to calculate unbiased weight and batter data interpretation that minimizes the total sum of the squared perpendicular distance from the points to the line (Rencher, 2002). There have been different scientific methods for determining the number of principal components to retain. In PCA algorithm, the number of principal components (PCs) have been determined based on a rule of thumb proposed by Kaiser (1960). According to that rule, a component will be retained if its eigenvalue is greater than unity. PCA is performed to calculate the components unbiased weight based on their factor scores and the proportion of variance of each component as described by Zhu et al. (2014) and Jolliffe (2002). In PCA analysis, prior to the PCs retention, several test statistics has been performed to assess the suitability of representative data. These tests include Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and range from 0 to 1 with $>$ 0.50 considered as suitable for PCA. The Bartlett's test of Shericity should be the level of significance with 'p' values less than 0.5 ($p < 0.5$) for PCA. Scree plot, is another method of PCs retention, explores the graphical interpolation method in decreasing order of eigenvalue with a line to determine the point at which the significant breakpoint exists (Cattell, 1966; Ledesma & Valero-Mora, 2007). Varimax rotation methods also applied which maximizes high item loadings and minimizes low item loadings thus providing more clear interpretation in a simplified way (Williams, Onsman & Brown, 2010).

3.6. Cluster analysis

The cluster analysis encompasses a number of algorithms and methods to identify structures within the data as a homogeneous group of cases. Cluster analysis has been applied to a wide range of research problems (Anderberg, 2014; Duran & Odell, 2013; Tan, Steinbach, & Kumar, 2013). In this study, the k-mean clustering method has been applied to produce much more stable cluster boundaries. In order to identify a reasonable optimal number of 'k' clusters, the sum of square

Table 2
The rationale of selecting socio-economic and bio-physical system indicators.

Sl.	Indicators (Conceptual basis)	Rationale
1	Density of population	Rapid growth of population lack in quality housing and living standard resulting an increase in vulnerability
2	Male-female ratio	Woman can be more sensitive during natural disaster and become vulnerable due to cultural structure and inferior social position.
3	Literacy rate	Increased literacy rate diminishes vulnerability by allowing access to information which enhances the coping ability.
4	Gender gap in literacy rate	Low female literacy rate partakes a terrific impact on sector specific employment with lower wages and threatens the stabilization of family planning.
5	Percentage of disable	Elderly and disabled face great risk of vulnerability because of obstruction in mobility and are most sensitive groups during natural hazards.
6	Source of drinking water	Households with access to improved source of drinking water are less susceptible to frequency of associated diseases to climate change.
7	Electricity connection	Access to electricity connection is fundamental to daily life as a tool of affordability to the quality of life and ensures socio-economic development.
8	Poverty	People below poverty line encounters great risk due lack in nutrition, health facilities and being exposed to environment during hazards.
9	Access to transport facilities	Improved transport system reduces vulnerability by facilitating early waning and disaster management.
10	Medical institutions	Important for rural health and hygiene practice contributing ultimate vulnerability reduction.
11	Govt. primary schools	Level of education is considered as an important determinant of socio-economic growth and represents adaptive capacity of a community.
12	Motor vehicles	Enriches level of urbanization and reduces vulnerability by moving to places with less risk.
13	Railway and water way	Increased overall communication networks reduce people's vulnerability by early warning systems in disaster risk management strategies.
14	Embankment roads	Embankment roads on coastal estuarine are considered as adaptive capacity providing an extensive economic and ecological services.
15	Cyclone shelters	Cyclone cause less damages to these shelters than the regular households. Cyclone shelter are likely to be less vulnerable to hazardous impacts of climate change.
16	Flood shelters	Flood shelter provides security to people in case of emergency and flood inundation taming the coping ability immediately after disaster.
17	Un- metalled roads	There is an essential correlation between access to roadway and better living. Increased road length progresses the adaptive capacity during emergency.
18	Co-operative societies	Region with better co-operational activities are presumed to be more able to adapt to climatic stresses.
19	Growth centers	Quality of infrastructure is an important measure of relative adaptive capacity. Higher the standard of infrastructures lower the risk of vulnerability.
20	Irrigation by power pumps	Irrigation is an important adaptation-enabler as it enables farmers save crops during dry spells or droughts. It is also strongly related to technology adoption. Groundwater is the primary source of drinking water to nearly half of the world's population and, as the dominant source of water to irrigated land, is critical to global food security.
21	Production of Rice	Higher crop and vegetable productivity and yield is directly proportional in reducing the vulnerability of the area by availability of more food being available and more income for farmers and thus their ability to cope with adversities.
22	Nationalized and private banks	Greater number of these banks implies easy credit to small and marginal farmers which performs a fundamental role in the development the rural economy.
23	Insurance companies	Recover from losses more quickly due to insurance, social safety nets, and entitlement programs.
24	Bank loan	The higher the percentage of total inhabitants get help from local banks and have access to income sources, the lesser the vulnerability.
25	Storm surge inundation (m)	Storm sure inundation increases the level of vulnerability with a potential impact on infrastructure.
26	Inundation due to riverine floods (m)	24-h flood map is used based on the potential severe damages that road, infrastructure, flood embankments, and rural houses usually are subject to from floods of such duration.
27	Shoreline erosion (m/year)	Shoreline change comparison is considered as increase in shoreline erosion increase vulnerability.
28	Shoreline accretion (m/year)	Coastal vulnerability decreases with shoreline accretion.
29	Coastal elevation (cm)	Coastal vulnerability decreases with coastal elevation.
30	1-day maximum rainfall (mm)	1-day maximum rainfall is considered as increase in maximum rainfall increase vulnerability.
31	Salinity intrusion due to SLR (%)	Salinity intrusion due to SLR is considered as increase in salinity increase vulnerability.

errors (SSE) metric (Zhang, Moges, & Block, 2016) has been determined in conjunction with the elbow method (Hamann, Biggs, & Reyers, 2015; Kashani & Graettinger, 2015). A good clustering with smaller 'k' can have a lower SSE than a poor clustering with higher 'k' (Tan et al., 2013). It has been found that 3 number of clusters can explain more than 72 percent variability having a SSE value less than 0.5. These three clusters are named as the low, medium and high scale with the range between 0.00 and 0.30, 0.40–0.70 and 0.80–1.00, respectively for both present and future cases. All the 140 coastal Upazilas have been expressed in terms of the three clusters: high, medium and low. Based on these optimal 3 clusters, the vulnerability scale maps have been generated.

4. Results and discussions

In this study, principal component analysis has been conducted to reduce variables quantities into a smaller number of variables-called principal components (PCs) as well as provides the useful information of original dataset as mentioned by Thompson (2004) and Williams, Brown, and Onsman (2012). A pairwise correlation matrix has been used in the PCA process visualizing the relations between respective variables to reduce the initial matrix to a subset of non-highly correlated metrics as described by Abson et al. (2012). Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy test value has found about 0.782 for present set and 0.648 for the future dataset. Bartlett's test of Shericity provides values of 0.000 for both cases indicates the suitability of these dataset and highly significant for running principal component analysis. The Kaiser' criterion with an eigenvalue greater than one (Kaiser, 1960) and Cattell scree test have performed to extract the number of principal components (PCs) (Cattell, 1966). In both cases, 7 principal components have been retained in present study that tabulated below in which Table 3 for present scenario as well as Table 4 for the future scenario. Tables 3 and 4 demonstrate the cumulative percentage of variance of 81 percent under present and 78 percent under future scenarios for 7 principal component (PCs) that having an Eigenvalue greater than one, respectively. Varimax orthogonal rotation method has been used for the PCA to develop principal component metrics which are uncorrelated to provide more meaningful data interpretation.

Unbiased weights have been found for each individual indicator

Table 3
List of retained principal component weights of all indicators for the present scenario.

Sl.	Indicators	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
1	Population density	0.077	0.023	-0.059	-0.082	-0.107	-0.005	-0.259
3	Literacy rate	0.496	0.287	0.269	-0.142	0.236	0.195	0.061
2	Male female ratio	0.251	-0.018	0.052	-0.139	0.0256	0.103	-0.511
11	Govt. primary schools	0.471	0.116	-0.471	-0.061	-0.399	0.235	0.007
4	Gender gap in literacy rate	0.785	0.123	0.09	0.188	-0.06	0.093	0.785
22	Nationalized and private banks	-0.065	0.869	-0.038	-0.066	0.052	-0.017	0.039
23	Insurance companies	-0.014	0.509	0.259	-0.161	-0.035	0.181	0.025
24	Bank loan	-0.048	0.860	0.038	-0.054	0.103	0.133	0.165
21	Production of rice	0.047	0.037	0.473	-0.164	0.213	0.107	0.107
20	Irrigation by power pumps	-0.157	0.021	0.553	-0.122	-0.058	0.034	-0.021
13	Railways and water ways	0.283	-0.015	-0.536	0.743	0.121	0.088	-0.125
6	Source of drinking water	0.022	0.018	0.067	0.763	-0.76	-0.005	-0.026
5	Percentage of disable	0.007	0.050	-0.017	0.008	0.507	0.026	-0.11
8	Poverty	-0.227	-0.083	0.023	0.316	0.328	0.144	-0.192
10	Medical institutions	-0.175	0.082	0.078	-0.009	0.777	-0.536	0.064
27	Shoreline erosion	0.019	0.013	-0.012	0.021	-0.035	0.521	-0.168
28	Shoreline accretion	0.109	0.104	-0.053	0.023	0.020	0.110	0.014
26	Inundation due to floods	-0.445	0.110	-0.180	0.101	-0.328	0.455	-0.051
25	Storm surge inundation	0.077	-0.031	0.021	-0.08	-0.119	0.777	-0.047
29	Coastal elevation	0.234	0.051	0.291	0.286	0.153	0.298	0.227
30	1-day maximum rainfall	-0.011	0.024	-0.035	-0.006	-0.099	0.332	0.023
31	Salinity intrusion due to SLR	-0.128	0.009	-0.110	0.702	-0.059	0.795	0.195
15	Cyclone shelters	-0.078	-0.115	0.152	-0.028	0.042	-0.014	0.723
16	Flood shelters	0.026	-0.030	0.030	0.067	-0.026	-0.055	0.087
18	Co-operative society	-0.113	0.285	-0.001	-0.191	0.031	0.023	0.484
7	Electricity connections	-0.525	-0.022	0.054	-0.212	0.024	-0.005	0.231
19	Growth centers	0.071	0.039	0.066	0.045	0.187	-0.025	0.464
9	Access to transport facilities	-0.165	-0.075	-0.586	-0.129	0.043	-0.055	0.709
17	Un- metalled roads	0.230	-0.046	0.066	0.097	0.005	-0.715	0.750
14	Embankment roads	0.065	-0.136	0.046	-0.758	0.253	0.063	0.782
12	Motor vehicles	0.046	0.551	0.057	0.048	-0.291	-0.083	0.554
	Eigenvalue	3.42	2.87	2.58	2.11	1.58	1.33	1.024
	Cumulative variability (%)	32	41	48	54	67	72	81

The heaviest loadings have been marked as bold shaded.

after carrying out PCA for the present period and shown in Table 2 in which 7 vulnerable groups as Principal Component 1 (PC1) to 7 (PC7) are tabulated with the loadings. In Tables 3 and 4, the heaviest loadings have been marked as bold shaded. Table 3 shows different types of vulnerabilities where 30 indicators have been arranged according to the highest value of PCA loadings. The 7 groups are titled with heavily loaded and termed them into vulnerability profiles: PC1 as Demographic Vulnerability, PC2 as Economic Vulnerability, PC3 as Agricultural Vulnerability, PC4 as Water Vulnerability, PC5 as Health Vulnerability, PC6 as Climate change & extremes Vulnerability, and PC7 as Infrastructural Vulnerability. Indicators of these groups are selected based on their heaviest loadings and marked by a bold shade in both Tables 3 and 4. The PC1 (Demographic Vulnerability) has been highly loaded by 5 indicators: population density, literacy rate, male-female ratio, govt. primary school, and the gender gap in literacy rate. The PC2 (Economic Vulnerability) has been loaded for 3 indicators which are nationalized and private bank, insurance company and borrowing money from a bank. The PC3 (Agricultural Vulnerability) has been loaded for 2 indicators which are rice production and irrigation by power pump. The PC4 (Water Vulnerability) has been loaded for 2 indicators which are the length of water ways and water source. The PC5 (Health Vulnerability) has been loaded for 3 indicators which are disable, poverty and medical institution. The PC6 (Climate change and extremes Vulnerability) has been loaded for 6 indicators: medical institution, inundation due to flood, storm surge inundation, coastal elevation, rainfall, and salinity intrusion. The PC7 (Infrastructural Vulnerability) was loaded for 9 indicators: cyclone shelter, flood shelter, cooperative society, electrified village, growth centers, transport facility, non-metallic road, length of embankment road, and motor vehicle. These 7 PC groups of vulnerabilities for both present (2013) and future scenario (2050) have been used to generate GIS maps to investigate their spatial distribution across the coastal region of Bangladesh. Figs. 2 and 3 demonstrate the present and future vulnerability scenario for the coastal region of Bangladesh based on PCA.

With a large and growing population and low adaptive capacity, coastal region of Bangladesh is highly vulnerable to extreme climatic events. The coastal region of Bangladesh has already experienced a major threat of socio-demographic vulnerability (PC1). The spatial discrete map provides an indication that the coastal region or Upazilas will be relatively more vulnerable considering the demographic

Table 4
List of retained principal component weights of all indicators for the future scenario.

Sl.	Indicators	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
1	Density of population	0.064	0.006	-0.019	-0.08	0.009	-0.079	-0.026
3	Literacy rate	0.419	0.281	0.288	-0.072	0.306	-0.131	-0.419
2	Male-female ratio	0.537	-0.002	0.008	0.021	0.348	-0.159	-0.537
11	Govt. primary schools	0.470	0.082	0.364	-0.049	0.078	-0.126	0.292
4	Gender gap in literacy rate	0.373	0.139	0.272	0.033	0.241	-0.334	-0.394
22	Nationalized and private banks	-0.068	0.877	0.023	0.001	0.053	-0.027	0.005
23	Insurance companies	-0.024	0.608	0.608	0.094	-0.094	-0.049	-0.031
24	Bank loan	0.056	0.855	0.073	0.034	0.103	-0.046	0.054
20	Irrigation by power pumps	0.055	0.040	0.665	-0.471	0.006	-0.350	0.119
21	Production of rice	-0.013	0.009	0.761	-0.761	-0.139	-0.100	0.103
6	Source of drinking water	0.012	0.031	0.080	0.783	-0.035	0.269	0.383
13	Railway and water way	0.073	-0.035	0.556	0.556	-0.492	0.010	0.098
5	Percentage of disable	-0.147	0.062	0.061	0.050	0.775	0.115	0.139
8	Poverty	-0.475	-0.116	0.147	-0.149	0.475	0.100	0.081
10	Medical institutions	-0.201	0.071	0.047	-0.114	0.778	-0.028	-0.104
26	Inundation due to floods	-0.635	-0.005	-0.091	-0.188	-0.498	0.635	-0.029
27	Shoreline erosion	0.005	-0.042	-0.064	-0.726	-0.135	0.726	0.076
28	Shoreline accretion	-0.198	0.098	-0.008	0.374	0.022	0.374	-0.003
25	Storm surge inundation	0.001	-0.054	-0.092	0.078	0.048	0.788	-0.049
31	Salinity intrusion	-0.933	0.032	0.085	0.071	-0.057	0.933	0.015
29	Coastal elevation	-0.913	0.032	0.085	0.071	-0.057	0.933	0.015
30	1-day maximum rainfall	-0.078	-0.024	-0.034	-0.112	0.052	0.552	-0.774
15	Cyclone shelters	0.001	-0.117	0.120	0.264	-0.740	0.040	0.663
16	Flood shelters	0.005	-0.052	-0.003	0.034	-0.031	0.016	0.813
18	Co-operative societies	0.037	0.288	0.093	0.048	0.067	-0.124	0.492
7	Electricity connections	-0.119	-0.004	0.273	-0.114	-0.571	-0.133	0.571
19	Growth centers	0.029	0.026	0.088	-0.019	-0.037	0.126	0.782
9	Access to transport facilities	-0.102	-0.093	-0.809	0.013	0.114	-0.041	0.809
17	Un- metalled roads	-0.029	-0.028	0.048	0.239	-0.179	0.120	0.706
14	Embankment roads	0.017	-0.111	-0.028	-0.175	-0.165	0.768	0.768
12	Motor vehicles	-0.115	0.506	-0.110	-0.139	-0.141	-0.131	0.546
	Eigenvalue	3.82	3.11	2.64	2.99	2.01	1.51	1.00
	Cumulative Variability (%)	28	36	44	58	62	69	78

The heaviest loadings have been marked as bold shaded.

changes in the future (Figs. 2(a) and 3(a)). The number of high and medium vulnerable coastal Upazilas has been increased from 53 to 61 and from 49 to 64 respectively from present to the future the under changing climate. However, the number of low vulnerable Upazilas reduced from 38 to 15 Upazilas from present to the future scenario (Table 5).

The economic vulnerability has been defined as greater economic distress in dealing with economic resource and losses, arising out of economic openness (Briguglio, Cordina, Farrugia, & Vella, 2009; Rosenblatt & Keller, 1983). In this study, the term economic vulnerability (PC2) has been defined as the lack of financial capital availability in the Banking and risks arising from lack of insurance coverages. The future vulnerability in the coastal region of Bangladesh will be significantly higher than present condition. Considering economic vulnerability from present to the future under the changing climate, the number of highly vulnerable coastal Upazilas has been increased from 14 to 22 (Table 5). The changes in economic vulnerability status of coastal Upazilas from present to the future is also depicted through spatial aggregation maps (Figs. 2(b) and 3(b)).

Climate change will create an additional stress and have direct a negative consequence on food security across the coastal belt. The crop production undergoes a change in most of the coastal Upazilas are aggravated by the extreme climate in the future. Extreme climate poses a significant threat to agricultural development. The high level of agricultural vulnerability (PC3) has been found in the study area as shown in spatial maps (Figs. 2(c) and 3(c)). High vulnerable coastal Upazilas will be increased from 41 to 57 whereas the low vulnerability region will be reduced from 22 to 17 (Table 5).

A large proportion of the population has already been experienced water vulnerability and raised the demand of water availability in most of the part of the world (Vörösmarty, Green, Salisbury, & Lammers, 2000). The coastal region of Bangladesh has already experienced an increasing demand of drinking water and freshwater requirements to maintain a healthy ecosystem. In the future, the number of highly vulnerable coastal Upazilas will be increased from 55 to 70 due to sea level rise and consequent saline water intrusion (Table 5). The spatial aggregation maps also depicted an increasing trend of water vulnerability of the study area (Figs. 2(d) and 3(d)).

The potential human health impacts of climate change are needed to inform the development of adaptation strategies, policies, and measures

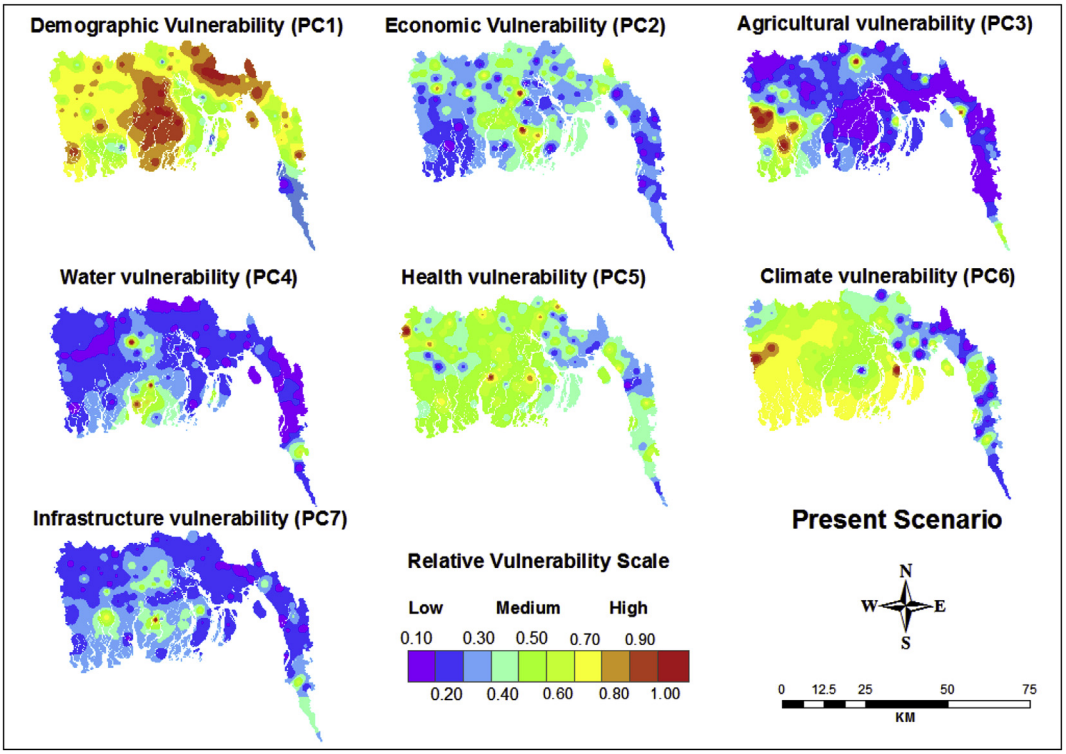

Fig. 2. Present (2013) vulnerability scenarios for the coastal region of Bangladesh.

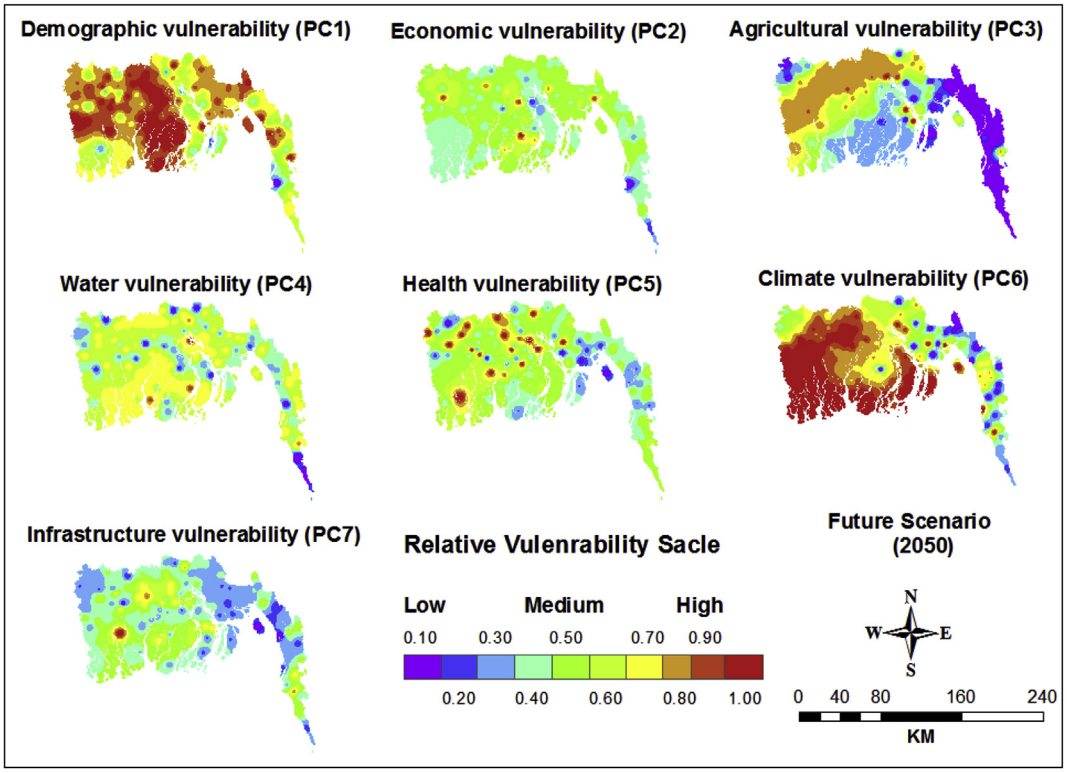

Fig. 3. Future (2050) vulnerability scenarios for the coastal region of Bangladesh.

to lessen projected adverse impacts (Ebi, Kovats, & Menne, 2006). Recent evidence suggests that the associated changes in temperature and precipitation are already adversely affecting public health (Sari Kovats, Menne, & Ebi, 2003). About 28 percent of the total population has lived in the coastal region of Bangladesh and highly vulnerable to health and wellbeing (PC5) due to the negative impact of climate variability and sea level rise. The spatial maps clearly show that most of the coastal region are highly vulnerable to health issues (Figs. 2(f) and 3(f)). Considering climate change, the number of highly vulnerable of coastal Upazilas will be increased from 46 to 65 while the low vulnerable

Table 5
Cluster analysis with relative vulnerability scale for 140 coastal Upazilas.

PCs	Vulnerability profile names	Relative vulnerability scale						Total No. of Upazilas
		High		Medium		Low		
		Present	Future	Present	Future	Present	Future	140
PC1	Demographic	53	61	49	64	38	15	140
PC2	Economic	14	22	82	78	44	40	140
PC3	Agricultural	41	55	77	68	22	17	140
PC4	Water	55	70	62	60	23	10	140
PC5	Health	46	65	46	85	47	12	140
PC6	Climate	60	88	40	22	40	30	140
PC7	Infrastructure	39	48	51	66	40	26	140

Upazilas will be reduced from 47 to 12 (Table 5).

Based on the findings from recent studies on this region, natural disasters such as cyclone, storm surge, floods, and drought will be more frequent and intense in the future. The climate vulnerability (PC6) will be enhanced in the coastal region of Bangladesh due to geographic settings, dense population, and poverty. The number of highly vulnerable of coastal Upazilas will be increased from 60 to 88 while the low vulnerable Upazilas will be reduced from 40 to 30.

Infrastructure related vulnerability (PC7) will also be higher in the future due to climate change. The climate-proof infrastructure will be required to combat climate change in the coastal region of Bangladesh. The number of highly vulnerable coastal Upazilas will be increased from 39 to 48 while low vulnerable Upazila will reduce from 40 to 26.

The use of PCA to derive multiple independent components of vulnerability from 30 indicators of sensitivity, exposure and adaptive capacity considering in the broad scale mapping is able to assess different components of the vulnerability. For present and the future scenarios under the changing climate, the pattern of the vulnerability of coastal Upazilas will also be changed. Composed by a combination of social, economic, physical and environmental factors, the assessment implies combining different domains and makes it therefore a challenge to identify a metric for vulnerability. Here, vulnerability has been defined in the context of climate change and developed spatial aggregation map of the multi-sectoral vulnerability profile in the coastal region of Bangladesh, which is largely prone to extreme climatic events (Kienberger, Lang, & Zeil, 2009). The high vulnerability and low adaptive capacity are a major concern in coastal regions of Bangladesh. People of coastal region lived exacerbate with health diseases and access to inadequate drinking water, infrastructure, and technology, degradation of natural resources and its ecosystem. It is needed to address the potential challenges of climate variability and extreme.

The South Asian region has been projected to be the worst suffers from the extreme events of climate change. Recent destructive flooding in 2016 and 2017 affected the low-lying floodplains and urban areas in Bangladesh, India, Nepal, Pakistan, Bhutan, and China. On the other hand, severe droughts and changes in seasonal rainfall patterns affected Pakistan, India, and Bangladesh. Wheat production in India decreased up to 50% by the end of the century while rice production in Bangladesh will be decreased by 30% at the end of the century. This will pose harmful impact the hundreds of the million people living in this region who rely on these two staple foods. This study also supports that vulnerability execrated by extreme climate change (PC6) in Bangladesh will be higher in the future. As there are verities of climate zones, diverse in landscape, the involvement of different sectors and actors, it's not so easy to combat climate effects without multilateral consensus to combat these problems in a sustainable way.

5. Conclusions

This study has identified 7 principal components through PCA which has been grouped as PC1 (Demographic Vulnerability), PC2 (Economic Vulnerability), PC3 (Agricultural Vulnerability), PC4 (Water Vulnerability), PC5 (Health Vulnerability), PC6 (Climate Vulnerability) and PC7 (Infrastructural Vulnerability). For all 7 PCA groups (termed as vulnerability profile), the number of high and medium vulnerable coastal Upazilas will be increased in the future. No of high vulnerable Upazila will increase from 53 to 61 for PC1, from 14 to 22 for PC2, from 41 to 22 for PC3, from 55 to 70 for PC4, from 46 to 65 for PC5, from 60 to 88 for PC6, from 39 to 48 for PC7, respectively. PCA based assessment of the vulnerability of the coastal region of Bangladesh demonstrates that different aspects of vulnerability are spatially discrete, with different areas characterized by different types of vulnerability. PCA technique for vulnerability assessment is found a very useful tool to identify vulnerable areas in the coastal region of Bangladesh considering both present and the future scenarios of climate change. The findings of this study might be useful for the policymakers as well as the planners of the country to combat the challenges posed by climate change.

This study also suffers from many limitations such as - i) same time period data was not available for every indicator chosen for this study, ii) as required data was not accessible during the study period, most of the data used have been compiled from secondary sources available in the public domain, iii) multiple regional model output for only extreme scenarios have been used for the climate projections, iv) all the impact models used have their own limitations in terms of mimicking the reality along with the coarse input data used, and v) output vulnerability maps are contingent with the choice of indicators retained and aggregation of datasets.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2018.12.011.

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